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The Relationship between Performance Degradation and Loss of Information caused by Lag Attributes on Collaborative Task Models in a Distributed Virtual Environment

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Abstract

In this paper, the modeling of efficiency in collaborative task carried out by two users on the Distributed Virtual Environment (DVE) is studied. The degradation of task performance, which is caused by the lag attributes such as the amount of lag, update interval and the fluctuation of lag, is modeled from a viewpoint of the range of integral calculation for conditional entropy. The subject experiments using two kinds of simple collaborative tasks for the purpose of the performance degradation and loss of information is carried out. As a result, the authors have found out that the amount of lag and update interval are the most and equally important factors for describing of task performance.

Key words: Distributed Virtual Environment, lag attribute, collaborative task, loss of information, maximum radius

1. Introduction

In recent years, there have been many reports of studies into virtual spaces that are shared across networks. These are known as Distributed Virtual Environments (DVEs) [1]-[10]. In the real-time systems seen in these references, the effects of communication lag can not be ignored. We also have confirmed this problem in references [11]-[13]. To make a system that is comfortable to use, these effects must be estimated beforehand.

In this paper we report on our experiments with a theoretical model of the performance (working time, work efficiency, etc.) degradation of collaborative tasks in a DVE where lag is present. Specifically, in a generalized task model, we have formulated a model of performance degradation due to the effects of latency based on parameters such as the amount of lag and the data reception interval (referred to as the update interval below). The model discussed here is expected to provide useful guidelines for the design of communication systems in the construction of DVEs.

2. Modeling performance degradation

2.1 Task model

A number of reports have already been made relating to the effects of network lag in real-time systems. For example, in references [1], [2] and [3] it has been confirmed that increased lag has an adverse effect on work. Also, in references [4] and [5] it has been confirmed that work is affected by the size and variation of update intervals. It has thus become clear that the efficiency of work is closely related to the amount of lag and the update interval. However, there have so far been no reports on the establishment of models that deal with these factors comprehensively. In this paper we will therefore try to consider them theoretically.

As the simplest example of a DVE, we will consider a model in which two users are present on a network. In this type of DVE, data is transmitted and received only between two users; user A on one terminal, and user B on the other terminal. Here, it is assumed that a collaborative task is performed in real time via objects manipulated by the users (referred to below as avatars). During this task, user A's terminal displays the attributes of the local avatar A that can be directly manipulated by user A, along with the attributes of the remote avatar B which is manipulated by user B. The two avatars are similarly displayed on user B's terminal. In this context, attributes refer to an avatar's physical properties (position, etc.) in a virtual space. The virtual space is assumed to be a space having physical attributes, and the avatar attributes are assumed to vary in a timewise and spatially continuous fashion due to the interactive operations of each user. The communication between the terminals is assumed to be asynchronous, with the most recent knowable information displayed on each terminal. The collaborative task to be modeled is assumed to be various types of teaching system as described in references [1] and [6]. Specifically, operation of each user is determined by the attributes of the remote avatar on a screen. In this paper, this sort of task is called a type of *mutual control* below, in the sense that operation of a local avatar is controlled by the remote avatar in vice versa. Moreover, it is assumed that lag factors relating to the manipulation and display of local avatars on local terminals can be negligible. Thus, in this issue, a problem of accuracy of user's manipulation, is not taken into account and the accuracy of remote avatar's attributes on the continuous time axis is analyzed. Examples of this includes the goodness of interactivity in the teaching system as described in references [1] and [6].

2.2 Loss of information and maximum radius

2.2.1 Loss of information and uncertainty

To perform a collaborative task smoothly under the assumptions in the previous section, the users have to accurately predict/estimate the remote avatar's simultaneous attributes, because the performance of this type of task is determined by the spatial accuracy of the attributes of the current remote avatar. The simultaneous attributes of the avatar would be available to the local terminal if there was no lag-i.e., the attributes of avatar A on terminal A and the attributes of avatar B on terminal B. Unless, the latest attributes are referred to as the latest one of the avatar that each terminal received. To make an accurate prediction/estimation, it is necessary to reduce the "uncertainty" relating to the remote avatar's latest attribute. Specifically, it is desirable that (a) there should be little difference between the attributes of the remote avatar as displayed on the local terminal's screen and the simultaneous attributes of the remote avatar (this is referred to as spatial uncertainty below), (b) the lag time between the transmission and display of attributes should be small (referred to as temporal uncertainty below), and (c) the update interval of the remote avatar's attribute should be small (referred to as temporal smoothness below).

In this paper we attempt a comprehensive treatment of these three types of factors from the viewpoint of the loss of information relating to the difference between simultaneous attributes of the remote avatar and latest attributes of it. We will start by introducing a coordinate system X relating to the attributes of the avatars in the DVE. In this coordinate system X, the vector representing the attributes of avatar A at time t is expressed as $A(t)$. Next we introduce a coordinate system Y in which a time axis is added to coordinate system X (Fig.1). Here, the time at which the ith set of data is received at terminal B is represented as t_i, and the lag incurred by the data received at t_i is represented as $\delta(t_i)$. In coordinate system Y, the coordinates of the remote avatar A observed at terminal B are expressed as $(A(t_i-d(t_i)), t_i-\delta(t_i))$, while the simultaneous coordinates of the remote avatar A at time t_i are expressed as $(A(t_i), t_i)$. In this paper it is assumed that the timings of the two terminals are matched. Accordingly, each user can work out the time stamp of the remote avatar's attribute information received at the local terminal.

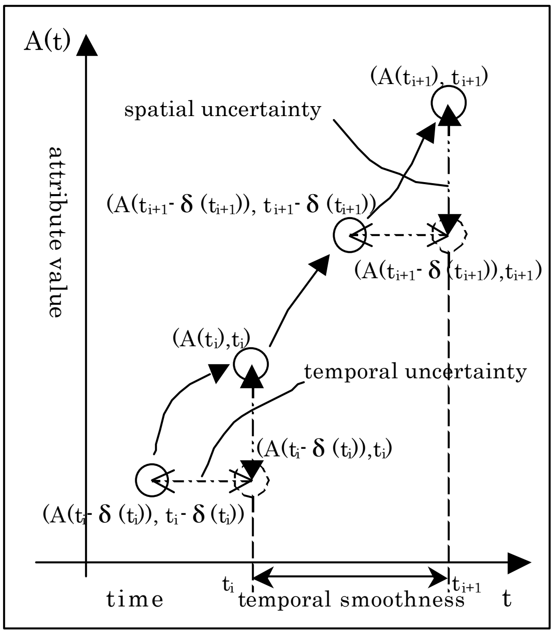

Fig.1 States of avatar A on coordinate system Y. The solid circles indicate the simultaneous avatar A, and the dashed circles represent the remote representation of avatar A displayed by terminal B.

Then, we consider the loss of information that occurs due to lag. We use the notation $P(a_1)$ to represent the probability of an event a_1 occurring at the present time t_i when the simultaneous attributes of the remote avatar are $A(t_i)$. The notation $P(a_1|a_2)$ denotes the probability of event a_1 occurring under conditions where the event a_2 occurred at time $(t_i-\delta(t_i))$ when the simultaneous attributes of the remote avatar were $A(t_i-\delta(t_i))$. At this time, the conditional entropy $I(a_1|a_2)$ is expressed as follows, where A_1 and A_2 are the sets of events a_1 and a_2 respectively, and $P(a_2)$ can be regarded as a constant:

$$I(a_1 \mid a_2) = -\sum_{a_a \in A_a} \sum_{a_2 \in A_2} P(a_2) P(a_1 \mid a_2) \log P(a_1 \mid a_2) \tag{1}$$

This conditional entropy $I(a_1|a_2)$ becomes larger with increasing the spatial uncertainty $|A(t_i)-A(t_i-\delta(t_i))|$ (the norm of the vector $A(t_i)-A(t_i-\delta(t_i))$ and temporal uncertainty $\delta(t_i)$. In other words, the temporal and spatial uncertainty relating to the attribute information of the remote avatar is thought to be governed by the distance between $(A(t_i),t_i)$ and $(A(t_i)\text{-}A(t_i\text{-}\delta(t_i)),t_i\text{-}\delta(t_i))$ in coordinate system Y. Therefore, if the distance between these two points is denoted by c and is expressed as a function of time by $c(t)$, then $c(t)$ can be expressed as follows:

$$c(t) = \left(\left| \alpha(t)\left(A(t) - A(t-\delta(t))\right) \right|^2 + \left(\beta(t)\delta(t)\right)^2 \right)^{1/2} \tag{2}$$

Where, $\alpha(t)$ and $\beta(t)$ are coefficients relating to the spatial and temporal uncertainty respectively, and are determined according to the nature of the task. Specifically, $\alpha(t)$ is a coefficient matrix (diagonal matrix) expressing the spatial precision of the required attributes. $\beta(t)$ is a (scalar) coefficient which represents the required temporal precision. Since the term $A(t)$ is unknown at time t, it is impossible to determine the value of $c(t)$ in Equation (2). We will therefore investigate the maximum and average values of this uncertainty.

2.2.2 Maximum value of uncertainty

We will first consider the maximum value that $c(t)$ can take. If v_{max} is a vector expressing the maximum change in the remote avatar's attribute vector per unit time, then $c_{max}(t)$-the maximum value of $c(t)$ occurring due to the change of avatar attributes-can be determined as follows:

$$c_{\max}(t) = \left(\left| \alpha(t) v_{\max}(t) \right|^2 + \beta(t)^2 \right)^{1/2} \delta(t) \tag{3}$$

Raising Equation (3) to kth power yields $r(t)$:

$$r(t) = c_{\max}(t)^k \tag{4}$$

Where, k is the number of dimension of an attribute vector. Based on Equation (4), we will consider the maximum value $H_{max}(a_1|a_2)$ of the amount of conditional self-information:

$$H(a_1 \mid a_2) = -\log P(a_1 \mid a_2) \tag{5}$$

In Equation (1), as $c_{max}(t)$ increases, the minimum value of $P(a_1|a_2)$ is thought to decrease. Therefore, $H_{max}(a_1|a_2)$ increases in monotonously proportion to the magnitude of $r(t)$.

2.2.3 Average value of uncertainty

Next we will consider the average value of the conditional self-information-i.e., the conditional entropy. For the sake of simplicity, we will evaluate Equation (1) for the case where k=1.

When the lag $\delta(t)$ at time t is equal to a small time period Δ, unless prior information is available, the remote avatar's attributes $A(t)$ can be assumed to describe a random walk following the discrete uniform distribution $U(A(t\text{-}\delta(t))\text{-}\varepsilon,\ A(t\text{-}\delta(t))+\varepsilon)$. Here, ε is taken to be the largest amount of change of the attribute that the user can bring about in the small time period Δ. Under this assumption, when the amount of lag is $\delta(t)=n\Delta$, the attributes $A(t)$ are thought to depend on the distribution calculated by the convolution of n uniform distributions, where n is a natural number. If this probability distribution is denoted by $f_n(x)$, then the maximum value of $f_n(x)$ occurs when $x=A(t\text{-}\delta(t))$, and x decreases as it gets further away from $A(t\text{-}\delta(t))$. On the other hand, the probability distribution $f_{n+1}(x)$ of the remote avatar's simultaneous values $A(t)$ when $\delta(t)=(n+1)\Delta$ is determined as the convolution of $f_n(x)$ with the uniform distribution:

$$f_{n+1} = f_n * U(x-\varepsilon, x+\varepsilon) \tag{6}$$

By comparing these two conditional entropy formulae:

$$I_n = -\sum_{f_n \in F_n} f_n \log f_n \tag{7}$$

$$I_n = -\sum_{f_{n+1} \in F_{n+1}} f_{n+1} \log f_{n+1} \tag{8}$$

it is clear that $I_n<I_{n+1}$. In these equations, F_n and F_{n+1} respectively represent the set of points on $c(t\text{-}n\Delta)$ centered on $A(t\text{-}n\Delta)$, and the set of points on $c(t\text{-}(n+1)\Delta)$ centered on $A(t\text{-}(n+1)\Delta)$.

2.2.4 Maximum radius cumulative function

It therefore follows that the maximum value $H_{max}(a_1|a_2)$ of the amount of conditional self-information and the conditional entropy $I(a_1|a_2)$ both increase as the lag increases. Here, $r(t)$ is related to the maximum value of the amount of information obtained when the remote avatar's attributes are ascertained under conditions where information is lost. For example, when the attributes are taken to be coordinate values in a 2D model, the size (area) of the region of possible attributes for the remote avatar is given by a circle of radius $c_{max}(t)$. And the distribution of f_n and I_n is shown in Fig.2 and Fig.3 when k=1.

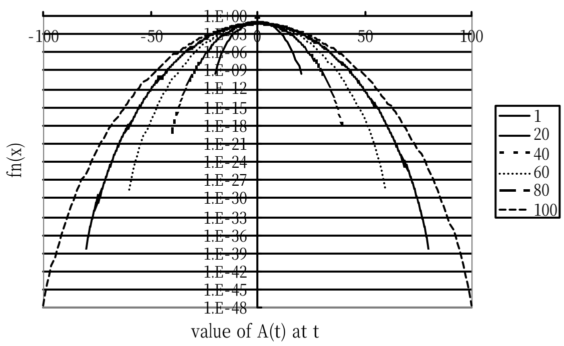

Fig.2 The Distribution of f_n in a 1D model. The horizontal axis is the changes of the attribute of $A(t)$ from $A(t\text{-}\delta(t))$, and the vertical axis is the probability of the existence about the $A(t)$ when $\delta(t)=n\Delta$.

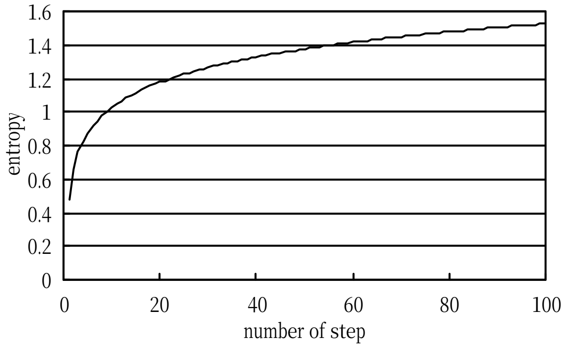

Fig.3 The value of I_n in a 1D model. The horizontal axis is the values of n when $\delta(t)=n\Delta$, and the vertical axis is the values of the conditional entropy I_n.

This term $r(t)$ is thus called the maximum radius function, in the sense that it is a function expressing the integral limit (referred to as the maximum radius below) when calculating the maximum loss of the information quantities at time t in the task. The cumulus of this maximum radius function $r(t)$ over the entire task is called the maximum radius cumulative function. If t_0 is the time at which the task begins and t_n is the time at which it ends, then this maximum radius cumulative function, denoted by $R(t_0,t_n)$ is expressed as follows:

$$R(t_0,t_n)=\int_{t_0}^{t_n} r(t)dt \tag{9}$$

Meanwhile, the limitations of communication capacity in current network environments result in constraints on the transmission intervals of the local avatar's attribute information [7]. This makes it impossible to present the attribute information of the remote avatar in timewise and spatially continuously. Thus-in addition to $r(t)$ which increases according to the magnitude of the lag-it is also necessary to consider the amount of increase in this radius, which continues to grow until the next information is received from the remote side. If $R(t_i,t_{i+1})$ is the cumulus of the radius from time t_i to time t_{i+1}, Equation (9) can be expressed as follows:

$$R(t_0,t_n)=\sum_{i=0}^{n-1} R(t_i,t_{i+1}) \tag{10}$$

If the time interval from time t_i until the next data is received is represented by $u(t_i)=t_{i+1}-t_i$, then Equation(10) can be calculated as follows, where Δ is the interval from time t_i to time t_{i+1}, and α and β are constants.

$$R(t_0,t_n)=\sum_{i=0}^{n-1} \int_{d(t_i)}^{d(t_i)+u(t_i)} \left(|\boldsymbol{a}(t_i)v_{\max}(t_i)|^2 + \boldsymbol{b}(t_i)^2 \right)^{k/2} t^k dt \tag{11}$$

This formula models the way in which the maximum radius increases with the age of the most recent information held by the terminal. Images for k=1 and k=2 are shown in Fig.4 and 5 respectively. In these figures, the area of the hatched regions is equivalent to $R(t_i,t_{i+1})$. As simple examples of this phenomenon, the models for k=1 and k=2 are described below.

(When k=1)

$$R(t_0,t_i) \le n\left(\overline{\boldsymbol{a}v_{\max}} + \overline{\boldsymbol{b}}\right)\left(\overline{\boldsymbol{d}u} + \frac{\overline{u}^2 + s_d^{\ 2}}{2}\right) \tag{12}$$

Here, $\overline{\boldsymbol{d}}$, $\overline{u}$, $\overline{\boldsymbol{a}}$ and $\overline{\boldsymbol{b}}$ indicate the average values of the amount of delay δ, the update interval u, and the coefficients α and β. Also, s_δ and s_u represent the standard deviations of δ and u. The following assumptions have been made here in order to simplify the model:

Assumption 1: There is no correlation between any of the each parameters δ, u, α and β.

Assumption 2: The transmission interval is more or less constant, and its magnitude is roughly equal to $\overline{u}$. Therefore $s_u \approx s_d$.

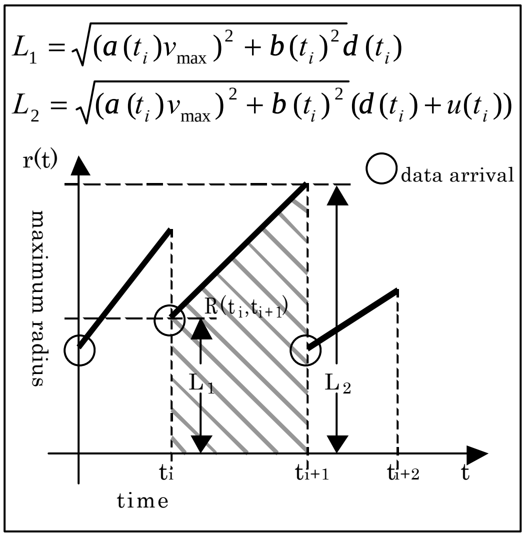

Fig.4 Growth of the maximum radius when k=1. The solid circle indicates the data arrival. The area of the hatched regions is equivalent to $R(t_i, t_{i+1})$.

(When k=2)

$$R(t_0,t_i) \approx n\left(\overline{|\boldsymbol{a}v_{\max}|^2} + \overline{\boldsymbol{b}^2}\right)\left(\frac{s_d^{\ 3} skw(\boldsymbol{d})}{3} + (2\overline{u}+\overline{\boldsymbol{d}})s_d^{\ 2} + \overline{u\boldsymbol{d}}(\overline{u}+\overline{\boldsymbol{d}}) + \frac{\overline{u}^3}{3}\right) \tag{13}$$

Here, $skw(\delta)$ represents the degree of skew in δ. Also $\overline{|\boldsymbol{a}v_{\max}|^2}$ and $\overline{\boldsymbol{b}^2}$ represent the mean-square values of $|\boldsymbol{a}v_{\max}|$ and β.

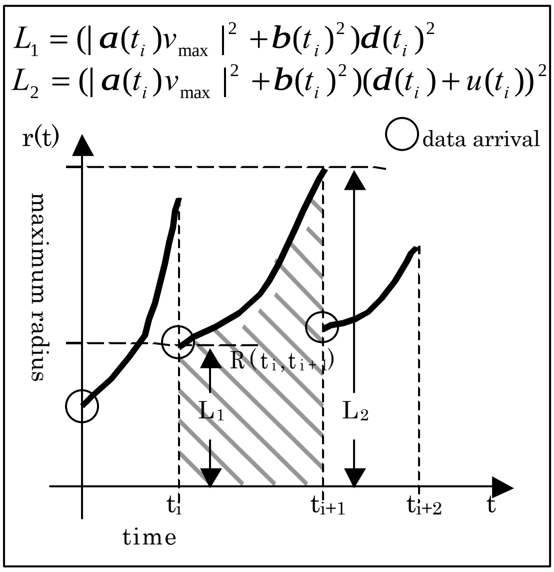

Fig.5 Growth of the maximum radius when k=2. The solid circle indicates the data arrival. The area of the hatched regions is equivalent to $R(t_i, t_{i+1})$.

2.3 Discussion

According to Equation (12) and (13), we assume s_{δ} should be smaller than $\bar{u}$ and found that the update interval mainly contributes to the cumulus of maximum radius in the most case. Specifically, when k=1 the formula for the cumulus of maximum radius includes terms that vary with the square of the magnitude of this parameter. And when k=2 it includes term that vary with the cube of their magnitude. Meanwhile, with regard to the amount of lag, contributions are also made by higher-order statistical quantities such as the fluctuation and skew of this parameter in addition to its magnitude.

On the other hand, if the amount of lag is greater enough than the update interval, we consider that the amount of lag and its fluctuation make greater contribution to it more than the update interval.

About the maximum radius, we consider that the update interval and the amount of lag make contribution to it.

We assume that the total sum of $\bar{d}$ and $\bar{u}$ is constant, and that the total of elapsed time is constant, we prefer that the case the lag should be smaller even if the update interval get larger.

In most mutual control type of task situations, it is considered that the maximum radius can be expressed by Equation (11), in which case it is possible to infer a rough task performance model by making suitable estimations for the coefficients α and β.

3. Experiment

3.1 Design of the experiments

In this paper, the following subject experiments for the purpose of studying the relationship between the degradation of the task performance and the loss of information is carried out. For the purpose of its study, two kind of simple collaborative tasks which are played in 1 or 2-dimensional space has been employed. As the experimental environment in this paper, DVE has two terminals on LAN is constructed. On the display in both terminals, both avatars are displayed, and they are colored by different color for examinees to enable to distinguish between local avatar and remote avatar. Both avatars are drawn on a task space as a small circle. A task in this experiment is required to consider the following 5 factors:

a) easy for the examinees to understand

b) easy to be influenced by lag

c) real time task

d) short elapsed time

e) collaborative task

Then, following type task is employed. Contents of a task given to examinees in this experiments was the tracking type task that one guides the other in a cooperative manner. In this task, an examinee of a pair, plays the role of a guide, and the other of a pair plays the role of a follower. An examinee of a guide is required to tell a follower the accurate tracking points presented from the system to only a guide in real time. And the examinee of a follower is required to follow the instruction from a guide. In the experiments, following two kinds of task have been employed. One is the task in 1-dimensional space (referred to below as 1D task), and the other is the task in 2-dimensional space (referred to below as 2D task).

Also in this paper, a problem of accuracy of user's manipulation is not taken into account. Therefore an avatar of a guide is manipulated automatically by the system in the experiments and it can follow the tracking point accurately.

The experimental measurement is the distance between two avatars in the task. This situation assuming that the coefficient of the spatial uncertainty is always constant in the task, and the coefficient of the temporal uncertainty is always zero.

3.2 System design

The system architecture for the experiments is shown in Fig.6. And the system parameters are:

A) The moving range of an avatar is 600 pixels.

B) The maximum velocity of an avatar is 80pixel / sec.

C) The refresh rate of the local avatar's state is always

20 fps.

D) The radius of an avatar is 20 pixels.

E) Analog type joystick is employed as a control device

F) Elapsed time of a task is 30 sec

Each parameter was defined empirically considering above 5 factors a) through e). The refresh rate of the local avatar's state was depended on the limitation of joystick's temporal resolution.

The tracking points are made by the Equation (14).

$$\begin{cases} x(t) = 300 + 125\sum_{n=1}^{4} \dfrac{\sin(2n\pi(t/30 + a_n))}{2^{n-1}} \\ y(t) = 300 + 125\sum_{n=1}^{4} \dfrac{\sin(2n\pi(t/30 + b_n))}{2^{n-1}} \end{cases} \quad (14)$$

Where t is the time from task starting, $x(t)$ and $y(t)$ are the x and y coordinates of the tracking point at time t (if in the 1D task, y coordinate is always constant), and a_n and b_n is given randomly in the range from 0 to 1 so that the total of move distance becomes 850〜950 in 1D task and 1350〜1450 in 2D task.

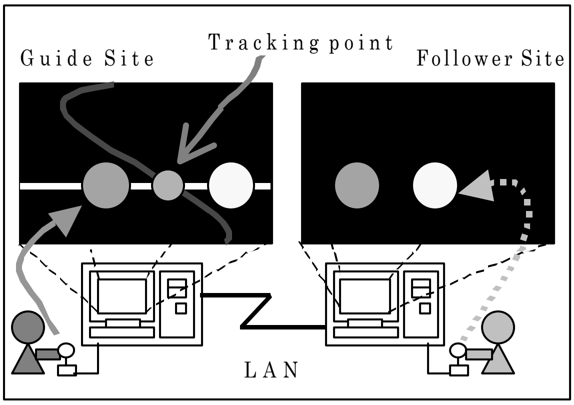

Fig.6 System architecture for the experiments

3.3 Task condition and lag models

Following 30 cases are examined in each task, and the difference between each case is analyzed. Constant lag, and Pareto distribution $f(x)=ak^a x^{-(a+1)}$ that is studied and proposed to apply as network lag model in references [14], were employed as lag models. In the Pareto distribution lag model, 2 levels of the fluctuations of lag (standard deviation) are employed. Specifically, the fluctuations are 25% or 50% in the average amount of lag. 3 levels of the update intervals, 3 levels of lag and 2 levels of the fluctuations of lag are employed. Hereafter, the case when constant lag is used, is referred to as Case A-δ-u. Where, δ and u mean the average amount of lag and the update interval respectively. The case when Pareto distribution type lag (25% fluctuation) is used, is referred to as Case B-δ-u, and the case when Pareto distribution type lag (50% fluctuation) is used, is referred to as Case C-δ-u.

3.4 Result

The experiment has been carried out in 9 examinees. Their ages ranged from 22 to 28. This experiment has been carried out after 3 or 4 times practices without lag. The order of the conditions is random for every examinee. The information given to the examinees beforehand was contents of a task and control method of an avatar. Existence of lags, model of lags, detailed information about task space and the manner of manipulation of a guide's avatar being automatic was not given.

The experimental results are shown in Table 1〜6, and Fig.7 and 8. For stability of trial, after 10 seconds had past since task start, it started to measure the distance. Each table and each figure shows the average value in all examinees of the average distance between the two avatars.

Table 1. Experiments result (1D task, unit is [pixel])

Case A		*update interval* [msec]		
		50	200	1000
lag [sec]	0	11.0	16.8	34.8
	0.5	24.3	29.3	44.8
	1	37.8	40.4	60.7
	2	56.4	58.6	69.6

Table 2. Experiments result (1D task, unit is [pixel])

Case B		*update interval* [msec]		
		50	200	1000
average lag [sec]	0.5	12.0	17.0	32.0
	1	27.1	30.6	46.2
	2	44.5	48.3	66.4

Table 3. Experiments result (1D task, unit is [pixel])

Case C		*update interval* [msec]		
		50	200	1000
average lag [sec]	0.5	9.6	15.3	33.2
	1	34.7	43.2	55.0
	2	53.4	63.0	80.0

Table 4. Experiments result (2D task, unit is [pixel])

Case A		*update interval* [msec]		
		50	200	1000
lag [sec]	0	21.9	27.9	57.6
	0.5	40.0	48.0	72.0
	1	56.4	70.3	84.9
	2	98.7	94.5	114.3

Table 5. Experiments result (2D task, unit is [pixel])

Case B		*update interval* [msec]		
		50	200	1000
average lag [sec]	0.5	20.3	25.4	56.2
	1	43.7	52.3	78.3
	2	70.6	78.7	103.4

Table 6. Experiments result (2D task, unit is [pixel])

Case C		*update interval* [msec]		
		50	200	1000
average	0.5	17.4	27.4	56.1
lag	1	53.5	64.5	89.7
[sec]	2	80.7	96.7	117.64

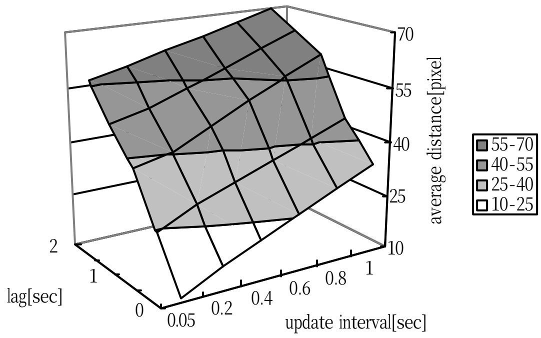

Fig.7 Comparison of the task performance degradation (1D task, Case A)

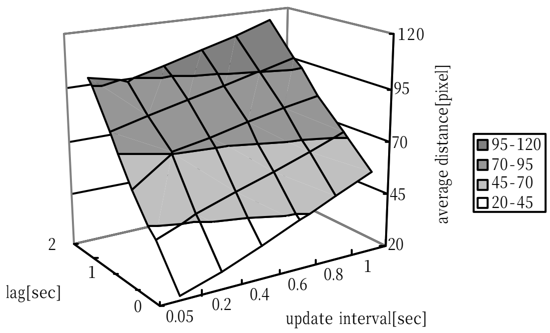

Fig.8 Comparison of the task performance degradation (2D task, Case A)

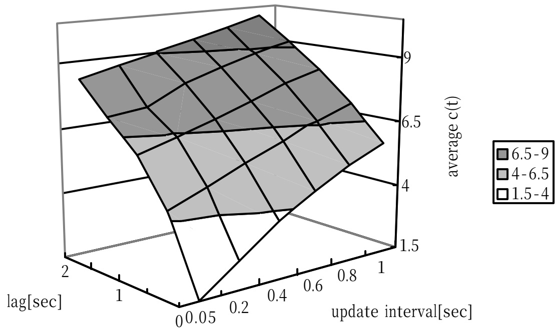

Fig.9 Theoretical model of average c(t)

3.5 Discussion

According to the result, with the lag increase, the tendencies of mostly linear increase of the average distance were seen in most cases. T-tests ($p<0.05$) about the difference of the average distance by the increase of the amount of lag were carried out. As a result, in Case A, there were significant differences except for the change from CaseA-1-1 to Case A-2-1. On the other hand, in Case B and C, there were significant differences except for the cases when the lag varies from 0[sec] to 0.5[sec].

Also with the update interval increase, the tendencies of mostly linear increase of the average distance were seen in most cases. T-tests ($p<0.05$) about the difference of the average distance by the increase of the update interval were carried out. As a result, there were significant differences in the cases when the update interval changed from 0.2[sec] to 1[sec] (except for the case between Case A-2-0.2 and Case A-2-1 in 1D task). On the other hand, there were not significant differences in the case when the update interval varies from 0.05[sec] to 0.2[sec]. It is thought that this difference in these tasks does not affect the task performance.

On the other hand, with the fluctuation increase, the tendencies of decrease of the average distance were seen in some cases. It seems that he influence by reductions of the amount of lag and its fluctuation was greater than the influence by the increase of the update interval when each terminal represent the received last information in these tasks. It is also related to the fact that the fluctuation has not selected independently of the other lag parameters. Moreover, it is thought as one of the reasons that the some increase of the update interval did not become bad influence for the subject since it was easier to predict the tracking point from the system than random work.

The performance degradation in these tasks is compared with the theoretical calculation result from Equation (2). Theoretical calculation of $c(t)$ was seen in Fig.9, when the random walk model was assumed as the tracking point. And $\alpha=1$ is assumed. Comparing Fig.7 with Fig.9, the shape of both graphs seems similar. This result might confirm the validity of the theoretical study. In Fig.8, the shape is less similar to Fig.9 than that the 1D task in Fig.7. The dissimilarity may come from the fact that the motion in 2D task is more difficult.

The fluctuation of lag is not studied enough in these experiments because the fluctuation becomes less than the update interval or the amount of lag. The evaluation on it is a future work.

4. Conclusion

In this paper we have modeled the performance degradation of collaborative tasks in a DVE based on parameters relating to lag. Next, we have tried to study the relationship between the degradation of the task performance and the information loss through the subject experiments. As the experimental results, we have confirmed the validities of theoretical model in the simple collaborative tasks employed in this paper. We have thereby taken the first steps toward an information theoretical analysis of the mutual control type of task space. And, proposed models are applicable to the field in real time system that has uncertainty about the information presentation, because the attributes in the model can be applied to the information from a man-machine system referred in [10].

In the future we plan to investigate and evaluate the validity of the model in the other type of task considering the fluctuation of lag, and design an adaptive prediction filter based on methods for inferring α and β in the task model and minimizing the maximum radius.

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